

①

Thu 4/11

Today: $R(\text{DISJ})$.

$$\text{DISJ}(x, y) = \text{NAND}(x_1, y_1) \wedge \text{NAND}(x_2, y_2) \wedge \dots \wedge \text{NAND}(x_n, y_n)$$

Let $\mu: x_1, \dots, x_n, y_1, \dots, y_n \text{ iid} \sim \text{Bernoulli}\left(\frac{1}{\sqrt{n}}\right)$.

Goal: $D_{\frac{1}{100}}^{\mu}(\text{DISJ}) \geq \text{large}$.

NB. We need μ to be "balanced" ($\mu(\text{DISJ}^{-1}(0)) = \Omega(1)$)

(Our choice satisfies this) $\rightarrow \text{Prob}_{\mu}(\text{DISJ}(x, y) = 1) \approx \frac{1}{e}$

Theorem: Under μ , $D_{\frac{1}{100}}^{\mu}(\text{DISJ}) = \Omega(\sqrt{n})$
(Babai-Frankl-Simon '86) (in fact $\Theta(\sqrt{n})$)

Coro: $R(\text{DISJ}) \geq \Omega(\sqrt{n})$.

Proof: Let Π_0 be a deterministic protocol s.t.

$$\Pr_{\substack{(x, y) \sim \mu \\ \text{the r.v.}}}(\text{DISJ}(x, y) = \Pi_0(x, y)) \geq 0.99$$

Let $\check{\Pi}(x, y)$ be the transcript of Π_0 on $(x, y) \sim \mu$.

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We

Know: $CC(\Pi_0) \geq \log_2 \left| \text{supp}(\Pi(X, Y)) \right|$

$$\geq H(\Pi(X, Y)) \stackrel{\downarrow}{=} I(X, Y; \Pi(X, Y))$$

(in fact =)

$$= I(X_1, \dots, X_n, Y_1, \dots, Y_n; \Pi(X, Y))$$

independence

$$\geq \sum_{i=1}^n I(X_i, Y_i; \Pi(X, Y))$$

Def: $\Pi_{a,b}^i = \Pi(X, Y)$ conditioned on $\begin{cases} X_i = a \\ Y_i = b \end{cases}$

P.S. 1, Problem 6 $\Rightarrow I(X_i, Y_i; \Pi(X, Y))$

$$\geq \mathbb{E}_{(a,b) \sim (\text{Ber}(\frac{1}{\sqrt{n}}))^2} \left[\Delta_{TV}^2 \left(\Pi_{a,b}^i, \Pi(X, Y) \right) \right]$$

(follows from Pinsker's ineq.)

Recall: $\Delta_{TV}(A, B) \triangleq \frac{1}{2} \sum_l |P_r(A=l) - P_r(B=l)|$

total var. distance

$$\Rightarrow I(X_i, Y_i; \Pi(X, Y)) \geq \frac{1}{\sqrt{n}} \left(1 - \frac{1}{\sqrt{n}} \right) \left[\Delta_{TV}^2 \left(\Pi_{10}^i, \Pi(X, Y) \right) + \Delta_{TV}^2 \left(\Pi_{01}^i, \Pi(X, Y) \right) \right]$$

$$\geq \frac{1}{4\sqrt{n}} \left(\Delta_{TV} \left(\Pi_{10}^i, \Pi \right) + \Delta_{TV} \left(\Pi_{01}^i, \Pi \right) \right)^2$$

triangle ineq $\geq \frac{1}{4\sqrt{n}} \cdot \Delta_{TV}^2 \left(\Pi_{10}^i, \Pi_{01}^i \right)$

③

$$\Rightarrow \frac{CC(\pi_0)}{n} \geq \mathbb{E}_i \left(I(X_i, Y_i; \pi(X, Y)) \right)$$

$$\geq \frac{1}{4\sqrt{n}} \mathbb{E}_i \underbrace{\Delta_{TV}^2(\pi_{10}^i, \pi_{01}^i)}_{(\text{Goal: } \geq \text{const})}$$

$$\geq \frac{1}{4\sqrt{n}} \left(\mathbb{E}_i \Delta_{TV}(\pi_{10}^i, \pi_{01}^i) \right)^2.$$

Two remaining parts:

① Argue, using the fact that π

is getting DIST right w.p. $\frac{99}{100}$, that
 $\mathbb{E}_i (\Delta_{TV}(\pi_{00}^i, \pi_{11}^i)) = \Omega(1)$.

② Prove that if $\Delta_{TV}(\pi_{00}^i, \pi_{11}^i) \geq \Omega(1)$,

then $\Delta_{TV}(\pi_{01}^i, \pi_{10}^i) \geq \Omega(1)$.

(Using rectangle property)

Clearly, we are done assuming ① and ②.

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For ①:

Note: $X_i = Y_i = 0 \Rightarrow \text{DISJ}(X, Y | X_i = Y_i = 0) = 1$
w.p. $\geq \frac{1}{4}$.

$\Rightarrow \Pr(\Pi_0 \text{ accepts given transcript } \Pi_{00}^i) \geq \frac{1}{5}$
($\frac{1}{4}$ -error prob.)

also: $X_i = Y_i = 1 \Rightarrow \text{DISJ}(X, Y) = 0$.

since i is also random (averaged),

we cover $\Omega(1)$ fraction of the prob. space

$\Rightarrow \mathbb{E}_i \Pr(\Pi_0 \text{ accepts given transcript } \Pi_{11}^i) \leq \frac{1}{6}$.

\Rightarrow Protocol is a good distinguisher (on average)

for Π_{00}^i and Π_{11}^i

Now we prove ②:

Rectangle Property: Fix i . We show $\exists A_0, A_1, B_0, B_1$
non-negative functions s.t.

s.t. $\Pr(\Pi_{ab}^i = \tau) = A_a(\tau) \cdot B_b(\tau)$.

Note: Inputs X^i, Y^i that lead to transcript τ

form a rectangle $R_\tau = S_\tau \times T_\tau$.

(5)

$$\begin{aligned} \Rightarrow \Pr(\Pi_{ab}^i = \tau) &= \Pr(X^i \in S_\tau \wedge Y^i \in T_\tau) \\ &\stackrel{X \text{ indep } Y}{=} \underbrace{\Pr(X^i \in S_\tau)}_{= A_a(\tau)} \underbrace{\Pr(Y^i \in T_\tau)}_{= B_b(\tau)}. \end{aligned}$$

Using this "product" property and some calculations, one can show (2).

$$\begin{aligned} \text{(2): } \sum_{\tau} |A_0(\tau) B_0(\tau) - A_1(\tau) B_1(\tau)| &\geq \Omega(1) \quad (p) \\ &\Downarrow \\ \sum_{\tau} |A_0(\tau) B_1(\tau) - A_1(\tau) B_0(\tau)| &\geq \Omega(1). \quad (p^2/2) \end{aligned}$$

NB: A_0, A_1, B_0, B_1 are prob. distributions.

$$\text{Def: } \Delta_{\text{Hel}}^2 \triangleq 1 - \sum_l \sqrt{\Pr(A=l) \Pr(B=l)}$$

(Hellinger distance)

In fact, this "dot product" is the Bhattacharya coefficient.

Exercise: (Using Cauchy-Schwarz)

$$\Delta_{\text{Hel}}^2(A, B) \leq \Delta_{\text{TV}}(A, B) \leq \sqrt{2} \Delta_{\text{Hel}}(A, B).$$

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Lemma: $\Delta_{\text{Hel}}^2(\pi_{00}^i, \pi_{11}^i) = \Delta_{\text{Hel}}^2(\pi_{01}^i, \pi_{10}^i)$.

Clearly, having the Lemma we are done with ②.

Proof of Lemma: Suffices to show the dot product of distributions remain the same.

$$\begin{aligned} & \Pr(\pi_{00}^i = \tau) \Pr(\pi_{11}^i = \tau) \\ &= A_0(\tau) B_0(\tau) A_1(\tau) B_1(\tau) \\ &= \underbrace{A_0(\tau) B_1(\tau)} \underbrace{A_1(\tau) B_0(\tau)} \\ &= \Pr(\pi_{01}^i = \tau) \Pr(\pi_{10}^i = \tau). \end{aligned}$$

□

* B.F.S. showed that every μ that is

a product distribution ($\mu(x,y) = \mu_{\text{Alice}}(x) \cdot \mu_{\text{Bob}}(y)$),

$$D^M(\text{DISJ}) = O(\sqrt{n} \log n).$$

So getting a better lower bound requires correlation.

⑦

Next time: $R(\text{DISJ}) = \Omega(n)$.

* This was first proved by Kalyanasundaram-Schnitger '87,

* Razborov '90 "Simplified" this.

* The proof we'll see is by Bar-Yossef -

- Jayram - Kumar - Sivakumar

2004

(Information-theory based).